

Supplementary Material:

Democratizing the Party: The Effects of Primary Election Reforms in Ghana
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The replication data and code are available at <https://doi.org/10.7910/DVN/FYOEWG>.

CONTENTS

Data	A2
Qualitative Interview Data	A2
Summary Statistics	A2
News Media Sources	A4
Missing Party-Constituencies	A4
Coding Aspirant Ethnicity	A4
Ethnic Diversity by Population Density	A6
Further Details on the Main Specification	A7
Aspirants and Nominees who are Female and from Non-Core Groups	A7
Matching Variables	A8
Matched Sets from Optimal Full Matching	A9
Excluding Aspirants Who Drop Out or are Disqualified	A9
Heterogeneous Effects by Constituency-Level Muslim Population Share	A10
Balance on Individual Matching Variables	A12
Heterogeneous Effects by Constituency Competitiveness	A14
Alternative Specifications and Estimation Procedures	A16
Differences-in-Differences	A16
Ordinary Least Squares	A17
Restricting the Number of Treated or Control Units in Each Set	A17
Matching with Calipers	A19
Analysis without Exact Matching on 2012 Outcome	A21
Alternative Matching Approaches	A22

DATA

Qualitative Interview Data

Qualitative information on the conduct of Ghanaian primaries is drawn from 155 interviews conducted by, or on behalf of, the authors with primary contestants in both major parties between 2010 and 2016. The most formal qualitative data collection involved an in-depth survey of 125 NPP primary aspirants competing in the party's 2015 primaries in advance of the 2016 elections. Because the NPP refused to provide us the contact information for its full slate of parliamentary aspirants, the survey sample is non-random and includes all aspirants in the NPP's 2011 primaries who competed again in 2015. The NDC refused to make similar contact information available, making it impossible to draw a similar sample of aspirants in the NDC's primaries before the 2016 elections. Ultimately, 125 of the 213 contacted NPP aspirants agreed to interviews. Almost all of the remainder were aspirants whose phone numbers had gone out of service since 2011 and could not be reached. The 2015 interviews were conducted by Ghanaian research assistants either over the phone or in person. These interviews were audio recorded and research assistants also entered responses into a questionnaire. Data gathered in our interviews is used to supplement the coding of biographical details from media sources for each of these aspirants.

Summary Statistics

Table A1 presents summary statistics for all variables used in the main specification and the alternative models.

TABLE A1: *Summary Statistics*

	<i>n</i>	Mean	SD	Min	Max
NDC:					
Total number of 2016 aspirants	219	3.52	1.65	1	9
Number of 2016 female aspirants	219	0.31	0.55	0	3
Number of 2016 non-core female aspirants	219	0.21	0.45	0	2
Num. 2016 aspirants from party's core ethnic groups	195	1.24	1.68	0	7
Num. 2016 aspirants from non-core ethnic groups	195	2.10	1.44	0	7
2016 nominee has only private sector background	219	0.23	0.42	0	1
2016 nominee is the incumbent	219	0.35	0.48	0	1
2016 nominee is female	219	0.14	0.35	0	1
2016 nominee belongs to party's core ethnic group	217	0.41	0.49	0	1
2016 nominee is non-core and female	216	0.09	0.29	0	1
Total number of 2012 aspirants	223	2.65	1.66	1	9
Number of 2012 female aspirants	223	0.29	0.58	0	3
Number of 2012 non-core female aspirants	220	0.18	0.47	0	3
Num. 2012 aspirants from party's core ethnic groups	211	1.28	1.54	0	7
Num. 2012 aspirants from non-core ethnic groups	211	1.29	1.22	0	6
2012 nominee has only private sector background	275	0.26	0.44	0	1

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Table A1 – continued from previous page

	<i>n</i>	Mean	SD	Min	Max
2012 nominee is the incumbent	275	0.30	0.46	0	1
2012 nominee is female	275	0.09	0.29	0	1
2012 nominee belongs to party's core ethnic group	217	0.41	0.49	0	1
2012 nominee is non-core and female	216	0.07	0.26	0	1
2016 incumbent's ethnic group share	104	0.55	0.34	0.003	0.97
Vote share in 2012 parliamentary election	269	0.48	0.16	0.13	0.92
Vote share in 2012 presidential election	268	0.53	0.19	0.14	0.96
Fractionalization of party's core ethnic groups	264	0.62	0.26	0.01	0.93
Segregation of party's core groups from other groups	264	0.18	0.11	0.00	0.56
Segregation among party's core groups	263	0.41	0.15	0.02	0.89
NPP:					
Total number of 2016 aspirants	252	2.87	1.57	1	8
Number of 2016 female aspirants	252	0.20	0.46	0	2
Number of 2016 non-core female aspirants	252	0.10	0.34	0.00	2.00
Num. 2016 aspirants from party's core ethnic groups	240	1.66	1.53	0	7
Num. 2016 aspirants from non-core ethnic groups	240	1.15	1.38	0	7
2016 nominee has only private sector background	252	0.32	0.47	0	1
2016 nominee is the incumbent	252	0.31	0.46	0	1
2016 nominee is female	252	0.08	0.27	0	1
2016 nominee belongs to party's core ethnic group	248	0.61	0.49	0	1
2016 nominee is non-core and female	245	0.02	0.13	0	1
Total number of 2012 aspirants	234	2.56	1.41	1	8
Number of 2012 female aspirants	234	0.34	0.59	0	3
Number of 2012 non-core female aspirants	230	0.18	0.42	0.00	2.00
Num. 2012 aspirants from party's core ethnic groups	222	1.59	1.49	0	8
Num. 2012 aspirants from non-core ethnic groups	222	0.94	1.18	0	6
2012 nominee has only private sector background	275	0.30	0.46	0	1
2012 nominee is the incumbent	275	0.29	0.45	0	1
2012 nominee is female	275	0.13	0.33	0	1
2012 nominee belongs to party's core ethnic group	271	0.61	0.49	0	1
2012 nominee is non-core and female	245	0.05	0.22	0	1
2016 Incumbent's ethnic group share	103	0.62	0.23	0.01	0.97
Vote share in 2012 parliamentary election	269	0.45	0.17	0.04	0.85
Vote share in 2012 presidential election	268	0.46	0.19	0.03	0.96
Fractionalization of party's core ethnic groups	263	0.51	0.27	0.04	0.89
Segregation of party's core groups from other groups	263	0.20	0.12	0.00	0.74
Segregation among party's core groups	262	0.40	0.23	0.01	1.00
Constituency:					
Pop density of constituency (log(1000s/sqkm))	264	1.85	5.52	0.01	49.86
Pop share of largest ethnic group in constituency	264	0.73	0.18	0.31	0.97

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Table A1 – continued from previous page

	<i>n</i>	Mean	SD	Min	Max
Muslim population share in constituency	264	0.17	0.21	0.01	0.98

News Media Sources

We use information from the following news sources in our coding: *The Ghanaian Chronicle* (independent newspaper), *The Daily Guide* (independent newspaper), *The Daily Graphic* (state-owned newspaper), *The Ghanaian Times* (state-owned newspaper), *Citi FM* (independent radio station), *Peace FM* (independent radio station), and *My Joy* (independent radio station), as well as modernghana.com, vibeghana.com, and ghanaweb.com, which are independently owned news aggregation websites. These sources span non-partisan outlets and those more aligned with each party.

Missing Party-Constituencies

We drop from our analyses party-constituencies where we do not feel confident that our media sources provide a full accounting of all primary aspirants for the 2016 elections. Out of 550 possible party-constituencies (275 constituencies * 2 parties), we drop 79, leaving 471 party-constituencies (219 NDC constituencies; 252 NPP constituencies) for our analysis. Table A2 presents *p*-values from simple t-tests for the difference-in-means between the missing and included party-constituencies on key covariates, including several measures of primary characteristics before the 2012 elections.

There are differences on some covariates. On average, the missing party-constituencies had slightly more aspirants competing in their 2012 primaries, had fewer incumbents re-nominated in 2012, were slightly more likely to have supported their party in the 2012 presidential (but not parliamentary) election, and have smaller Muslim population shares. But the missing and included party-constituencies are similar on all of the other covariates.

Coding Aspirant Ethnicity

We code the ethnicity of each aspirant based on their names, which are generally easily connected to the main ethnic categories in Ghana. We assign ethnicity based on a dictionary of 3,503 names of Ghanaian politicians, comprising aspirants in the 2011-2012 NDC and NPP primaries as well as all candidates in the 2010 district assembly (city council) elections in Greater Accra Region, which as Ghana's largest urban area has numerous candidates from all major ethnic groups.

Each name in the dictionary was coded in triplicate into ethnic categories by a team of five university-student research assistants in Accra who come from different regions of the country and ethnic groups. Anglophone name fragments that lack ethnic content (e.g., "John") were removed, but Anglophone surnames were left in the dictionary, since these frequently indicate Fanti ethnicity. The dictionary was then matched to the list of aspirants, and each aspirant was assigned the ethnicity of the majority coding of matches to her name. This allows us to identify the overall ethnic category for 87% of the 2015 primary aspirants and over 90% of the 2011-2012 aspirants. Importantly, this method can easily distinguish Ghanaian names among 7

TABLE A2: Comparing missing to non-missing party-constituencies.

Variable	Differences in means (missing – non-missing)	<i>p</i> -value
Total number of aspirants, 2012	0.57	0.03
Number of female aspirants, 2012	0.07	0.39
Num. aspirants from non-core groups, 2012	0.06	0.74
Female nominee, 2012	-0.03	0.46
Incumbent was nominee, 2012	-0.12	0.01
Private-sector only nominee, 2012	0.04	0.39
2012 parliamentary vote share	0.03	0.14
2012 presidential vote share	0.05	0.03
Ethnic fractionalization of core groups	0.00	0.92
Muslim % (constituency)	-0.05	0.01
Population density (constituency)	1.10	0.16

broad categories – Akan (excluding Fanti), Fanti, Ga-Dangme, Ewe, Guan, and Northern – but cannot reliably distinguish ethnic sub-groups within these categories. For example, a name such as “Kwame Owusu” is clearly identifiable as Akan, but could not be consistently coded among Akan subgroups. For Northern names, there are too many small Northern ethnic groups with their own naming conventions for the research assistants to be able to systematically tell them apart.

Ethnic Diversity by Population Density

Figure A1 plots two measures of constituency-level ethnic diversity – overall ethnic fractionalization (left panel) and ethnic fractionalization among core ethnic groups of each party (right panel) – against constituency population density (logged 1000s/sq km). Population density is moderately correlated with both diversity measures, with more diversity in denser (i.e., more urban) constituencies: $r = 0.25$ for the correlation of overall ethnic fractionalization and population density, while $r = 0.16$ for the correlation of intra-party fractionalization and population density. But Figure A1 shows that, using either measure, there are still many rural constituencies with low population density but significant ethnic diversity.

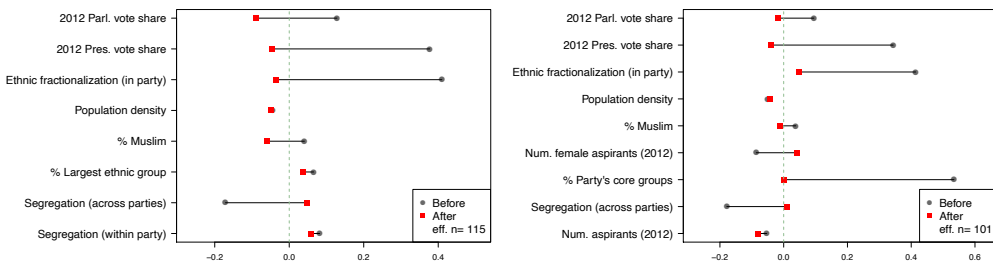


Figure A1: Ethnic diversity measures by logged constituency population density.

FURTHER DETAILS ON THE MAIN SPECIFICATION

Aspirants and Nominees who are Female and from Non-Core Groups

For the number of female aspirants from non-core groups, we match on a propensity score calculated from the matching variables used for the number of female aspirants and the matching variables used for the number of aspirants from non-core groups, as well as the lagged dependent variable. We estimate that the average effect on the number of female aspirants from non-core groups is 0.12 ($p < 0.01$). For whether the nominee is female and also from a non-core group, we match a propensity score calculated from the matching variables used for the whether the nominee is female and the matching variables used for whether the nominee is from a non-core group, as well as the lagged dependent variable. The estimated effect is an 8 percentage-point increase in the probability the NDC nominee was female and from a non-core group ($p < 0.01$). Figure B1 shows the balance on individual matching variables. Although the sample sizes become small, Table B1 shows that these effects are not concentrated in constituencies where the party has little chance of winning.



(a) Number of non-core, female aspirants

(b) Nominee is female and non-core

Figure B1: Balance on individual matching variables for intersectional outcomes: the x-axis displays standardized differences in means on each variable.

TABLE B1: Heterogeneous Effects for Intersectional Outcomes by Constituency Competitiveness.

Outcome	Subset	Estimate	S.E.	p -value	n_T	Sets
Num. Non-Core, Female Aspirants	Full data	0.17	0.04	< 0.01	168	84
	Non-competitive	0.09	0.04	0.05	57	35
	Competitive	0.08	0.05	0.10	61	31
	Stronghold	0.08	0.07	0.29	49	14
Nominee is Female & Non-Core	Full data	0.08	0.02	< 0.01	169	76
	Non-competitive	0.09	0.03	< 0.01	57	25
	Competitive	0.06	0.03	0.04	63	31
	Stronghold	0.02	0.02	0.32	44	14

Matching Variables

All models match exactly on the 2012 value of each outcome variable and an outcome-specific propensity score. We are not able to match party-constituencies on pre-2012 trends, for example dating back to the 2000 or 2004 elections. Unfortunately, there is too much missingness in our data for the pre-2012 primaries to implement such a model without restricting analyses to a very small and unrepresentative set of observations. We would also lose additional observations because new constituency boundaries were introduced between the 2008 and 2012 elections and we cannot define 2008 and 2004 primary outcomes for constituencies that did not previously exist.

The following four variables are always included in the calculation of the propensity score: the party's vote share in the 2012 presidential election in the constituency; the party's vote share in the 2012 parliamentary election in the constituency; the constituency population density; and ethnic fractionalization among the aligned ethnic groups of the party in the constituency.

As noted in the main text, for the total number of aspirants from core or non-core ethnic groups the set of matching variables also includes the size of the largest ethnic group in the constituency, segregation between ethnic groups associated with the NDC and the NPP, and segregation among the sub-groups within each party's national ethnic coalition. The first measure of segregation compares the geographic segregation of Northerners, Ewes, and Ga-Dangmes together from Akans (excluding the Fanti). The second measure of segregation captures the spatial distribution of the sub-groups among the Northerners, Ewes, and Ga-Dangmes for NDC primaries and the spatial distribution of the sub-groups within the Akan for NPP primaries.

We include the segregation measures because as primary electorates expand and competition shifts towards promises about the delivery of local public goods and away from vote buying, segregation can affect primary voters' beliefs about which types of candidates are most likely to target them with local public goods. This in turn could affect whether additional aspirants from new ethnic groups enter the primaries looking to better represent their co-ethnics' interests by bringing local public goods to their areas in a constituency. Voters often expect a politician to favor his or her own ethnic communities in the delivery of these goods. This will still benefit voters from other groups living in the same area when ethnic groups are residentially integrated because the benefits of local public goods are non-excludable within local communities (Ejdemyr et al. 2018). But where there is greater ethnic segregation, local public goods targeted to a politician's own group will not benefit other ethnic groups, increasing incentives for these other groups to seek their own co-ethnic MP who will instead target them with benefits. This dynamic accounts for significant variation in vote choice in Ghanaian general elections (Ichino and Nathan 2013). Ethnic segregation within each party's coalition, as well as ethnic segregation between each party's core groups and other ethnic groups in the constituency, may thus affect the extent to which primary competition is polarized along ethnic lines, altering the incentives of politicians from these groups to come forward as aspirants.

We measure segregation using Theil's spatial information theory index H , which is equal to 0 at complete integration and the even spatial distribution of ethnic groups, and to 1 at complete segregation (Reardon and O'Sullivan 2004). This is also known as the multigroup entropy index, and it is the weighted average deviation of each enumeration area's entropy from the constituency entropy. For a constituency with G ethnic groups, each with population share π_g , the entropy of the constituency is $E = \sum_{g=1}^G (\pi_g) \ln(\frac{1}{\pi_g})$. The entropy of an enumeration area k is $E_k = \sum_{g=1}^G (\pi_{gk}) \ln(\frac{1}{\pi_{gk}})$, where π_{gk} is ethnic group g 's population share in enumeration area k . H for a constituency can then be expressed as $\sum_{k=1}^K \frac{n_k(E - E_k)}{nE}$, where n_k is the total population

of the enumeration area k and $n = \sum_{k=1}^K n_k$ is the total population of the constituency with K enumeration areas. We use `seg v0.5-1` in R v3.3.1 to calculate H (Hong 2014).

For whether the nominee is a core ethnic group member we add: the constituency population share of the ethnic groups in the party's core coalition, the segregation of these ethnic groups associated with the party from all other ethnic groups in the constituency, and the number of aspirants from these party-associated groups who competed in the 2012 primary. Including these three additional variables helps account for potential heterogeneity in the effects of the NDC's reforms on the types of nominees who win primaries. Aspirants from ethnic groups outside of the party's core ethnic base may find it more difficult to win a primary in constituencies where the party's core ethnic base makes up a larger proportion of the population. Aspirants from non-associated groups may also have a more difficult time winning primaries in segregated constituencies where voters from the party's core groups may be less likely to believe they will benefit from local public goods promised by non-coethnics. Finally, the baseline number of aspirants from each ethnic group can affect the probability a candidate from that group wins under the new rules, since it affects whether an additional aspirant from a particular ethnic group would split the group's votes.

Matched Sets from Optimal Full Matching

We prefer optimal matching to nearest-available (greedy) matching algorithms that may be more familiar to political scientists. With the latter, the ordering of the units matters since a control unit that is matched to a treated unit becomes unavailable for matching to another treated unit later on. This can be particularly consequential when the number of available control units is limited as in our study.

Figure B2 shows sets of treatment and control units created by our main specification with optimal full matching for the total number of aspirants; for this example, we show only those sets for units that had 3 aspirants in the 2012 primaries. Treated (NDC) units are in dark green and control (NPP) units are in blue, with the weight of each unit represented by the area of its circle. The units are sorted by their propensity score, which does not include the total number of aspirants in the previous election (on which we exact match). Note that all treated units (green) are weighted the same. Line segments join units of one treatment status to units of the other treatment status within the same matched set.

Excluding Aspirants Who Drop Out or are Disqualified

Our main analysis counts as aspirants any primary contestants who file nomination forms to compete in the primary. But for each party and each election year, some of these aspirants drop out before the primary actually occurs, while others are formally disqualified by party leaders during the vetting process, as described in Ichino and Nathan (2012). There may be concern that our estimated effects on the entry of new types of aspirants (i.e., women, non-core ethnic groups) are primarily driven by "hopeless" aspirants who initially decide to enter the primary because of the uncertainty created by the NDC's new rules, but then drop out before the primary election date as they realize they are not viable candidates.

We believe this alternative explanation is unlikely for two reasons. First, it cannot account for our result that significantly more women and aspirants from non-core ethnic groups go on to win nominations due to the NDC's reforms. This strongly suggests that many of these new

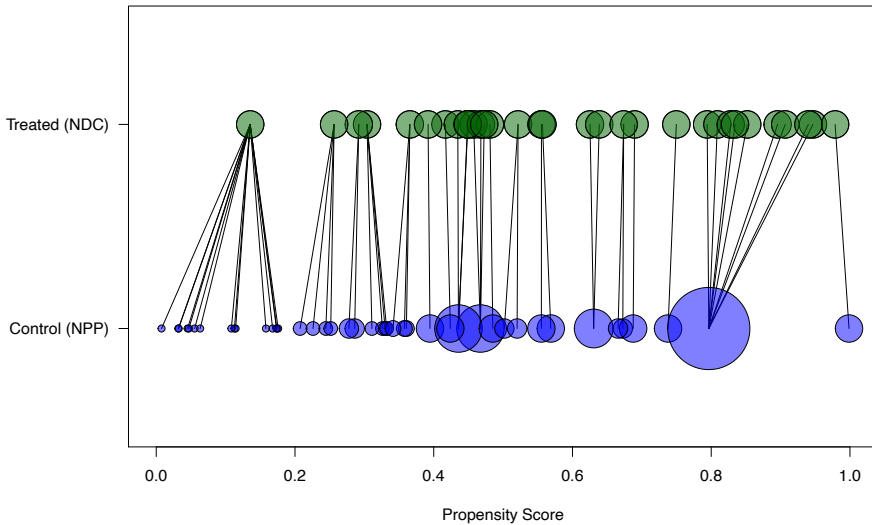


Figure B2: Matched sets for total number of aspirants among units with 3 aspirants competing in the 2012 primaries. The area of each circle represents the weight assigned to each unit.

aspirants were viable contestants. Second, our coding of the media reports allows us to identify which specific aspirants dropped out or were disqualified through the vetting process before the actual primary was held. At least one initial aspirant dropped out before the primary in 131 NDC primaries and 39 NPP primaries leading into the 2016 elections. In Figure B3, we re-do our main analyses for the number of aspirants from non-core groups, the number of female aspirants, and the total number of aspirants after excluding all aspirants who dropped out or were disqualified. We show our original estimates from Figure 1 in the main text for comparison (in blue). Our point estimates remain very similar, and our main findings that the NDC's reforms increased the entry of female aspirants and of aspirants from non-core ethnic groups are still statistically significant at conventional levels. Even after adjusting for all drop outs, Figure B3 confirms that the NDC's reforms led to new types of aspirants competing in its primaries.

Heterogeneous Effects by Constituency-Level Muslim Population Share

Table B2 reports estimates of the effect of the reforms on whether the nominee is female in constituencies that have below and above median Muslim population shares (9.5%).

TABLE B2: *Estimated ATT on Whether Nominee is Female.*

	Estimate	S.E.	<i>p</i> -value	n_T	Sets
Nominee is Female (Low Muslim)	0.14	0.04	< 0.01	78	54
Nominee is Female (High Muslim)	-0.03	0.03	0.32	92	36

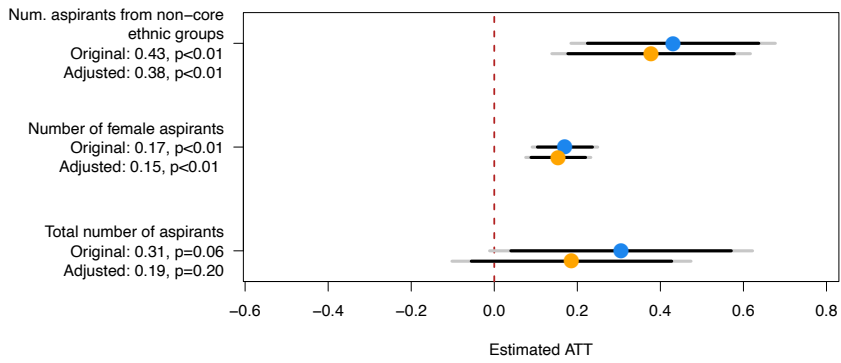


Figure B3: Results for number of aspirants, removing aspirants who dropped out or were disqualified before the primary (adjusted estimate; orange). Original estimates in blue for comparison.

Balance on Individual Matching Variables

Figures B4 - B6 present standardized mean differences on individual matching variables before and after optimal full matching, using `xBalance` in the package `RItools` version 0.1-15 in R version 3.6.2 (Bowers et al. 2016). Before matching, this is the difference in means between treatment and control divided by the pooled standard deviation for each covariate. After matching, the within-set difference in means is weighted in proportion to the harmonic mean of the number of treated units and control units in the set (Hansen and Bowers 2008).

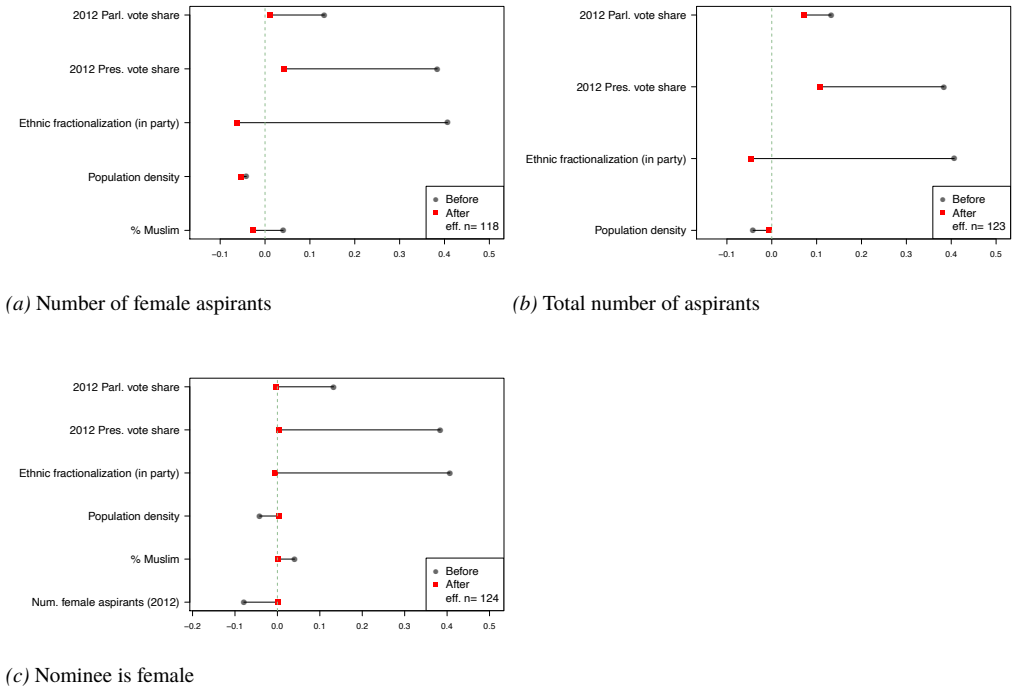
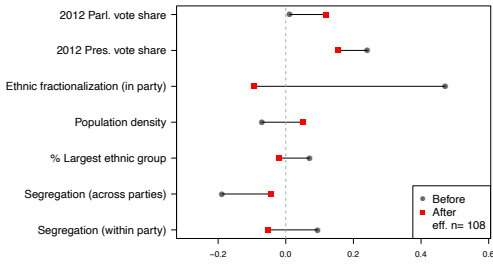
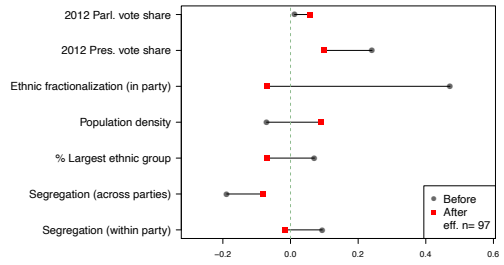


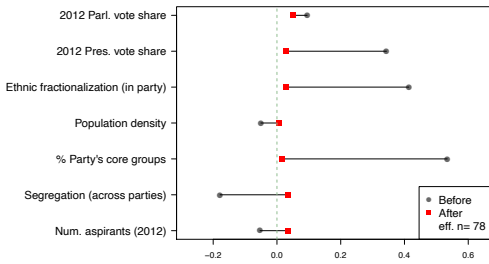
Figure B4: Balance on individual matching variables for gender-related outcomes and total number of aspirants: the x-axis displays standardized differences in means on each variable.



(a) Number of aspirants from non-core groups

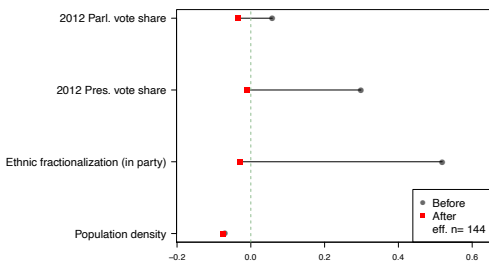


(b) Number of aspirants from core groups

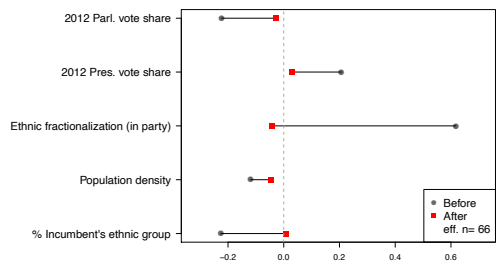


(c) Nominee is from a core group

Figure B5: Balance on individual matching variables for ethnicity-related outcomes: the x-axis displays standardized differences in means on each variable.



(a) Nominee has only a private sector background



(b) Nominee is the incumbent

Figure B6: Balance on individual matching variables for outcomes related to political experience: the x-axis displays standardized differences in means on each variable.

Heterogeneous Effects by Constituency Competitiveness

In Table B3 we report heterogeneous effects by three levels of electoral competitiveness: non-competitive constituencies in which the party received less than 45% in the 2012 parliamentary election; competitive constituencies where the party received between 45% and 55%; and stronghold constituencies where the party received more than 55%. We rematch for each outcome within each strata of competitiveness. We report estimates from Figure 1 in the main text using the full data for comparison. The last two columns give the number of treated units remaining and the number of sets created by optimal full matching. Table B3 shows that our main results are not concentrated exclusively in “hopeless” (i.e., non-competitive) seats for each party.

TABLE B3: *Heterogeneous Effects by Constituency Competitiveness.*

Outcome	Subset	Estimate	S.E.	<i>p</i> -value	<i>n_T</i>	Sets
Num. Female Aspirants	Full data	0.17	0.04	< 0.01	168	89
	Non-competitive	0.20	0.06	< 0.01	57	36
	Competitive	0.12	0.07	0.09	62	30
	Stronghold	0.18	0.09	0.05	48	18
Total Number of Aspirants	Full data	0.31	0.16	0.06	170	95
	Non-competitive	0.71	0.24	< 0.01	57	28
	Competitive	0.14	0.24	0.56	63	33
	Stronghold	0.61	0.32	0.06	45	20
Nominee is Female	Full data	0.08	0.02	< 0.01	170	97
	Non-competitive	0.09	0.04	0.01	57	35
	Competitive	0.02	0.03	0.49	63	32
	Stronghold	0.11	0.05	0.04	50	20
Number of Aspirants from Non-Core Ethnic Groups	Full data	0.43	0.12	< 0.01	150	83
	Non-competitive	0.17	0.21	0.42	52	32
	Competitive	0.86	0.18	< 0.01	56	28
	Stronghold	1.37	0.26	< 0.01	28	10
Number of Aspirants from from Core Ethnic Groups	Full data	-0.21	0.12	0.09	148	77
	Non-competitive	0.15	0.17	0.39	52	28
	Competitive	0.18	0.21	0.41	56	24
	Stronghold	0.18	0.28	0.52	40	15
Nominee is a Core Ethnic Group Member	Full data	-0.22	0.03	< 0.01	170	54
	Non-competitive	-0.05	0.05	0.35	57	19
	Competitive	-0.12	0.06	0.05	63	24
	Stronghold	0.02	0.05	0.70	50	8
Nominee has Private Sector Background	Full data	-0.11	0.03	< 0.01	211	114
	Non-competitive	-0.21	0.04	< 0.01	81	45
	Competitive	-0.00	0.04	0.93	73	37
	Stronghold	-0.00	0.02	1.00	57	28
Nominee is the Incumbent	Full data	0.17	0.06	< 0.01	102	53
	Competitive	0.12	0.09	0.21	46	21
	Stronghold	0.22	0.08	0.01	51	24

ALTERNATIVE SPECIFICATIONS AND ESTIMATION PROCEDURES

Differences-in-Differences

The standard linear differences-in-differences (DD) model is an alternative approach to estimating the ATT. The DD model and the lagged dependent variable model make different identifying assumptions, and the choice of models depends on whether one believes the most important omitted variables are time invariant or not. The DD is a fixed effects approach that differences out unspecified unmeasured time-invariant variables. Without weighting using covariates, this is simply the difference between the average of the changes in the outcomes for the NDC primaries from 2012 to 2016 and the average of the change in the outcomes for the NPP primaries from 2012 to 2016. This is also equivalent to pairing the NDC to the NPP in *each* constituency and calculating the differences in outcomes, since the difference of averages is the same as the average of differences. It relies on a “parallel trends” assumption, which we are unable to check because we only have data for two time periods (2016 and 2012) due to redistricting ahead of the 2012 elections.

By contrast, our preferred approach emphasizes what we think is a more important time-varying omitted variable – the normalization or expectation of the feasibility of success of aspirants from under-represented groups – through a proxy of the 2012 (i.e., lagged) outcome. Having female aspirants or nominee in the previous primary demonstrates that a path to political office may be open for women in that constituency. The same argument applies to having aspirants or a nominee from a non-core ethnic group. Our approach reflects the belief that this normalization is an important part of the model for the counterfactual. We would implement a lagged dependent variable model if data for additional elections were to become available, as potential aspirants would adjust their expectations as outcomes are realized. However, the models in this analysis are very similar because we only have two time periods and all our covariates are measured only at one point in time (for example, from the 2010 census).

TABLE C1: *Estimated ATT with Differences-in-Differences.*

	Estimate	S.E.	<i>p</i> -value
Number of female aspirants	0.17	0.07	0.02
Total number of aspirants	0.57	0.20	0.01
Nominee is female	0.08	0.04	0.04
Num. aspirants from non-core ethnic groups	0.45	0.17	0.01
Num. aspirants from party’s core ethnic groups	0.09	0.18	0.62
Nominee belongs to party’s core ethnic group	0.03	0.05	0.61
Nominee has only private sector background	-0.07	0.04	0.07
Nominee is the incumbent	0.04	0.09	0.68

We can estimate the ATT in the DD framework by regressing the outcome on an indicator for NDC, year, and their interaction, and our matching variables. Table C1 reports the coefficients on the interaction term, the estimates of the ATT for each outcome, from regressions that include covariates. Six of the 8 results are signed in the same direction as the results in our preferred analysis; the two that are signed in the opposite direction have *p*-values greater than 0.6. The DD-estimated effects are very similar to our main specification for (a) the number of aspirants

from non-core ethnic groups, (b) number of female aspirants, (c) whether the nominee is female, and (d) whether the nominee has only a private sector background. The DD-estimated effect is much larger than our full optimal matching-estimated effect for the (e) total number of aspirants.

Ordinary Least Squares

Table C2 reports the coefficients on the NDC variable from OLS regressions. For each outcome, the matching variables and the lagged outcome are included as controls.

TABLE C2: *Estimated ATT with OLS.*

	Estimate	S.E.	<i>p</i> -value
Number of female aspirants	0.13	0.05	0.02
Total number of aspirants	0.49	0.19	0.01
Nominee is female	0.08	0.03	0.01
Num. aspirants from non-core ethnic groups	0.68	0.15	< 0.01
Num. aspirants from party's core ethnic groups	-0.14	0.16	0.39
Nominee belongs to party's core ethnic group	-0.17	0.04	< 0.01
Nominee has only private sector background	-0.11	0.03	< 0.01
Nominee is the incumbent	0.04	0.07	0.61

Restricting the Number of Treated or Control Units in Each Set

As a robustness check, we restrict matched sets to have at most 1 treated to 10 control or 10 treated to 1 control units (Tables C3 and C4). Note that the left side of Table C3 ("Before matching") simply replicates the left side of Table 1 from the main text. The balance is not quite as good as in our main specification, but the results are substantively similar.

TABLE C3: *Balance before and after full optimal matching with restrictions on the number of treated or control units in each set.*

	Before matching			After matching		
	χ^2	df	<i>p</i> -value	χ^2	df	<i>p</i> -value
Number of female aspirants	92.13	6	< 0.01	5.27	5	0.38
Total number of aspirants	94.31	5	< 0.01	8.88	4	0.06
Nominee is female	92.51	7	< 0.01	2.22	6	0.90
Num. aspirants from non-core ethnic groups	79.51	8	< 0.01	6.47	7	0.49
Num. aspirants from party's core ethnic groups	92.10	8	< 0.01	6.91	7	0.44
Nominee belongs to party's core ethnic group	168.19	8	< 0.01	21.54	7	< 0.01
Nominee has only private sector background	116.41	5	< 0.01	4.08	4	0.39
Nominee is the incumbent	57.78	6	< 0.01	4.96	5	0.42

TABLE C4: *Estimated ATT, with restrictions on the number of treated or control units in each matched set.*

	Estimate	S.E.	<i>p</i> -value	n_T	Sets
Number of female aspirants	0.17	0.04	< 0.01	168	87
Total number of aspirants	0.27	0.16	0.09	170	95
Nominee is female	0.08	0.02	< 0.01	170	97
Num. aspirants from non-core ethnic groups	0.46	0.12	< 0.01	150	83
Num. aspirants from party's core ethnic groups	-0.20	0.12	0.11	148	73
Nominee belongs to party's core ethnic group	-0.28	0.04	< 0.01	169	60
Nominee has only private sector background	-0.09	0.02	< 0.01	211	114
Nominee is the incumbent	0.10	0.06	0.08	102	53

We can further show that there are significant advantages to allowing matched sets to have variable numbers of treated and control units, with some sets having many constituencies from one party being matched to just one constituency from the other party. If we conduct optimal matching with the restriction that only one control unit be matched to each treated unit (pair matching), significant imbalances remain (Table C5).

TABLE C5: *Imbalance remains after optimal pair matching.*

	χ^2	df	<i>p</i> -value	n_T	Sets
Number of female aspirants	70.67	5	< 0.01	168	168
Total number of aspirants	75.13	4	< 0.01	168	168
Nominee is female	77.98	6	< 0.01	170	170
Num. aspirants from non-core ethnic groups	51.68	7	< 0.01	137	137
Num. aspirants from party's core ethnic groups	49.85	7	< 0.01	119	119
Nominee belongs to party's core ethnic group	91.95	7	< 0.01	152	152
Nominee has only private sector background	104.64	4	< 0.01	210	210
Nominee is the incumbent	46.71	5	< 0.01	95	95

Matching with Calipers

We set caliper restrictions and re-estimate our models. The caliper restricts matched sets to party-constituencies falling within c standard deviations of each other on the propensity score. In Figure C1, we vary c from 0.1 to 1.5 standard deviations and present the estimated effects with their 90% and 95% confidence intervals. For comparison, our original effect estimates are represented by the dashed blue horizontal line in each panel. The red diamonds indicate the number of treated units remaining after optimal full matching with calipers. Larger numbers of treated units with no available matches from the control group are discarded when the calipers are set to be very small.

There are small variations in estimated effect sizes depending on the caliper size. But overall, the main results for most outcomes hold consistently across most caliper sizes, suggesting that these results are not due to extrapolation or interpolation from poor overlap.

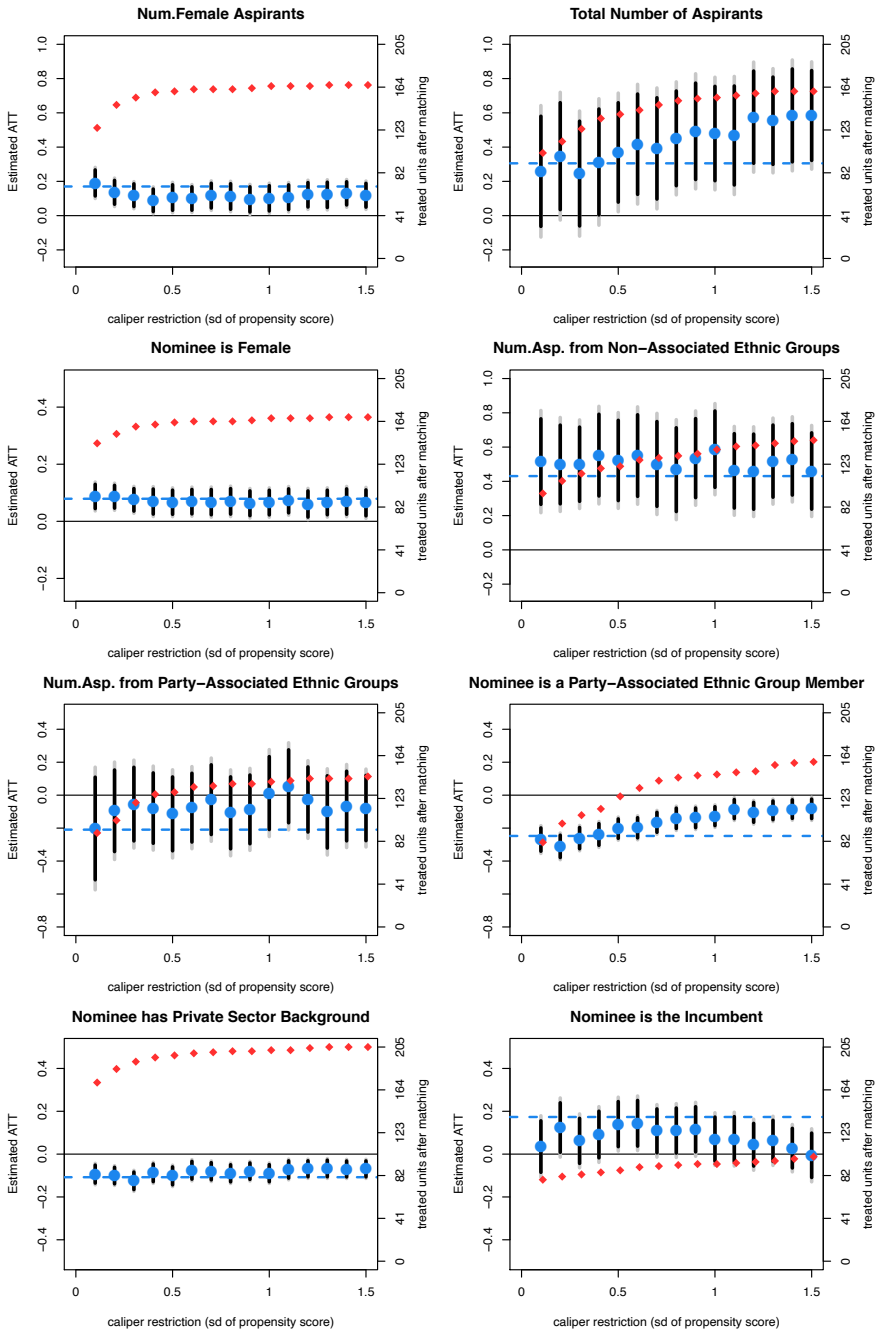


Figure C1: Estimated average effects after optimal full matching with calipers.

Analysis without Exact Matching on 2012 Outcome

Figure C2 shows that all except one of our results hold when we no longer require exact matches on the 2012 value of each outcome variable. The estimate for the average effect on the number of female candidates is still signed in the same direction, but no longer statistically significant at conventional levels. Corresponding balance statistics are in Table C6.

TABLE C6: Overall Balance without Exact Matching on 2012 Outcome.

	χ^2	df	p-value	n_T	Sets
Num. Female Aspirants	0.48	6	1.00	170	93
Total Number of Aspirants	0.15	5	1.00	170	94
Nominee is Female	0.97	7	1.00	170	96
Num. Asp. from Non-Associated Ethnic Groups	2.66	8	0.95	150	82
Num. Asp. from Party-Associated Ethnic Groups	6.43	8	0.60	150	77
Nominee is a Party-Associated Ethnic Group Member	0.85	8	1.00	169	55
Nominee has Private Sector Background	1.54	5	0.91	211	113
Nominee is the Incumbent	1.83	6	0.93	102	50

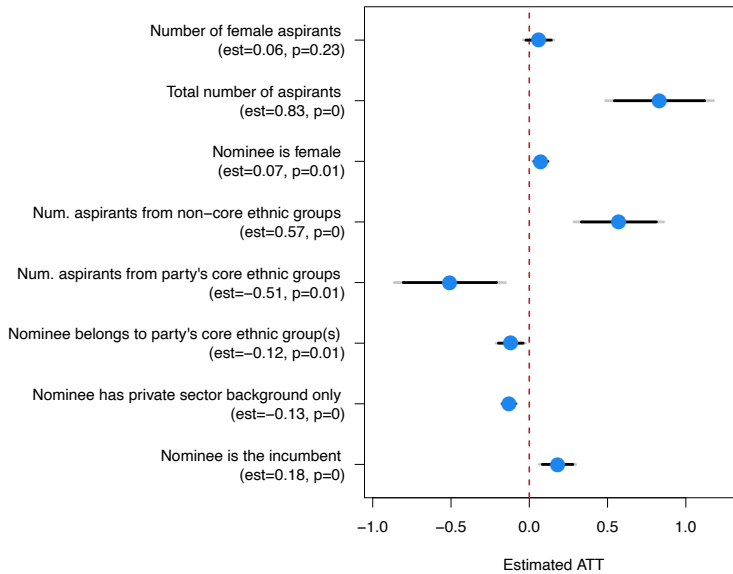


Figure C2: Estimated average effects after matching, without exact matching on 2012 outcome.

Alternative Matching Approaches

A variety of matching methods are available for applied research. Figures C3 and C4 present summaries of balance and the estimated ATT using optimal full matching (our preferred model), along with three matching methods with 1:1 matching – propensity score matching with a logit model to calculate the propensity score, multivariate matching using Mahalanobis distance, and genetic matching. The first two of these alternative methods are popular in social scientific research, while the third method uses a genetic search algorithm to look for the optimal weight to be given to each covariate and can be considered a generalization of the first two methods.

For each outcome, we use the same set of matching variables as in the main specification, including exact matching on the 2012 value of the outcome variable, and we match, with replacement, one control for each treated unit. We use regression to estimate the ATT while adjusting for bias and report Abadie-Imbens standard errors. These are implemented with the package `Matching` version 4.9-6 in R, version 3.6.0 (Sekhon 2011).

For each method, we have 8 outcomes, each with their own set of matching variables. We summarize the covariate balance achieved by each of these methods in Figure C3, with each panel corresponding to a different matching method (or no matching). Each panel is a frequency distribution of the absolute value of the standardized mean difference between treatment and control for each of the individual matching variables for all eight outcomes. For the panel on optimal full matching approach, the numerator is a weighted average of within-stratum differences in means on the covariate. Each panel is a histogram of the absolute values of the magnitudes represented by the red squares in the two figures from the subsection on “Balance on Individual Matching Variables”. The dashed line in each panel indicates the mean of these absolute values for each method. We can see that all four matching methods improve balance by this measure, shifting the distributions towards zero from the baseline of no matching, but that optimal full matching is notably more successful than the other three approaches. We thus prefer optimal full matching because it produces better balance than the alternatives.

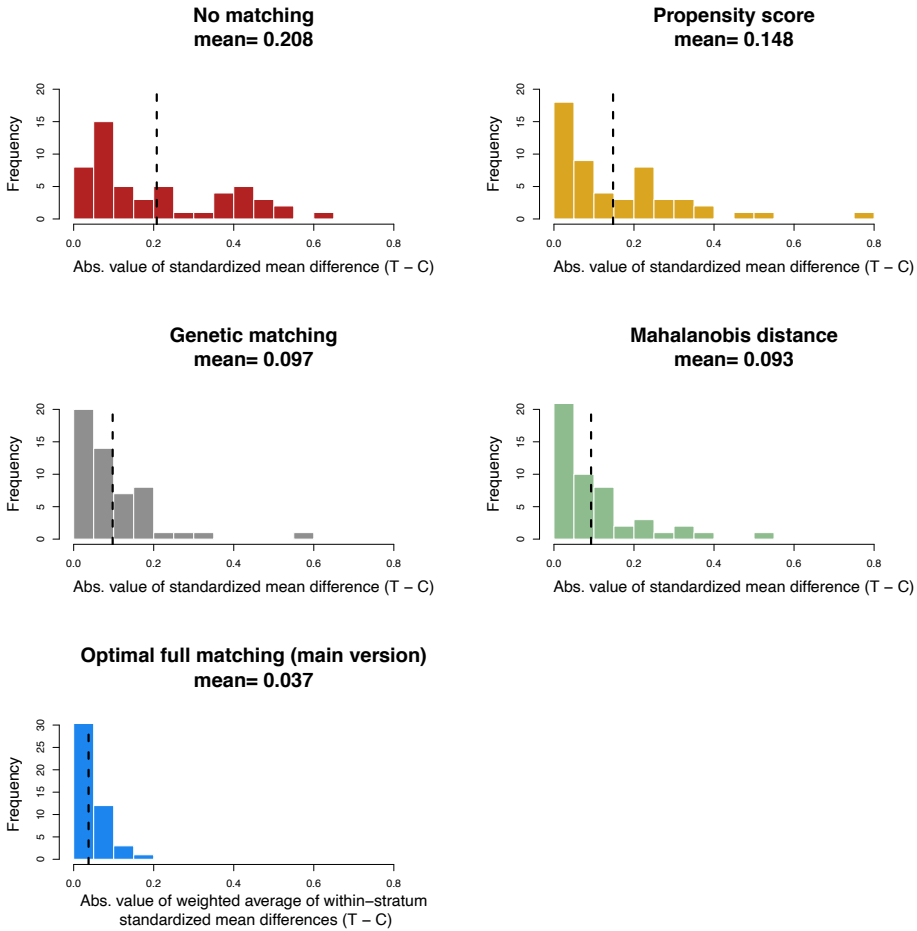


Figure C3: Summary of Balance on Individual Matching Variables with Alternative Matching Methods. Each panel summarizes a different matching method. The dotted line indicates the average of the absolute values of the standardized mean differences between treatment and control on all the individual matching variables for all eight outcomes.

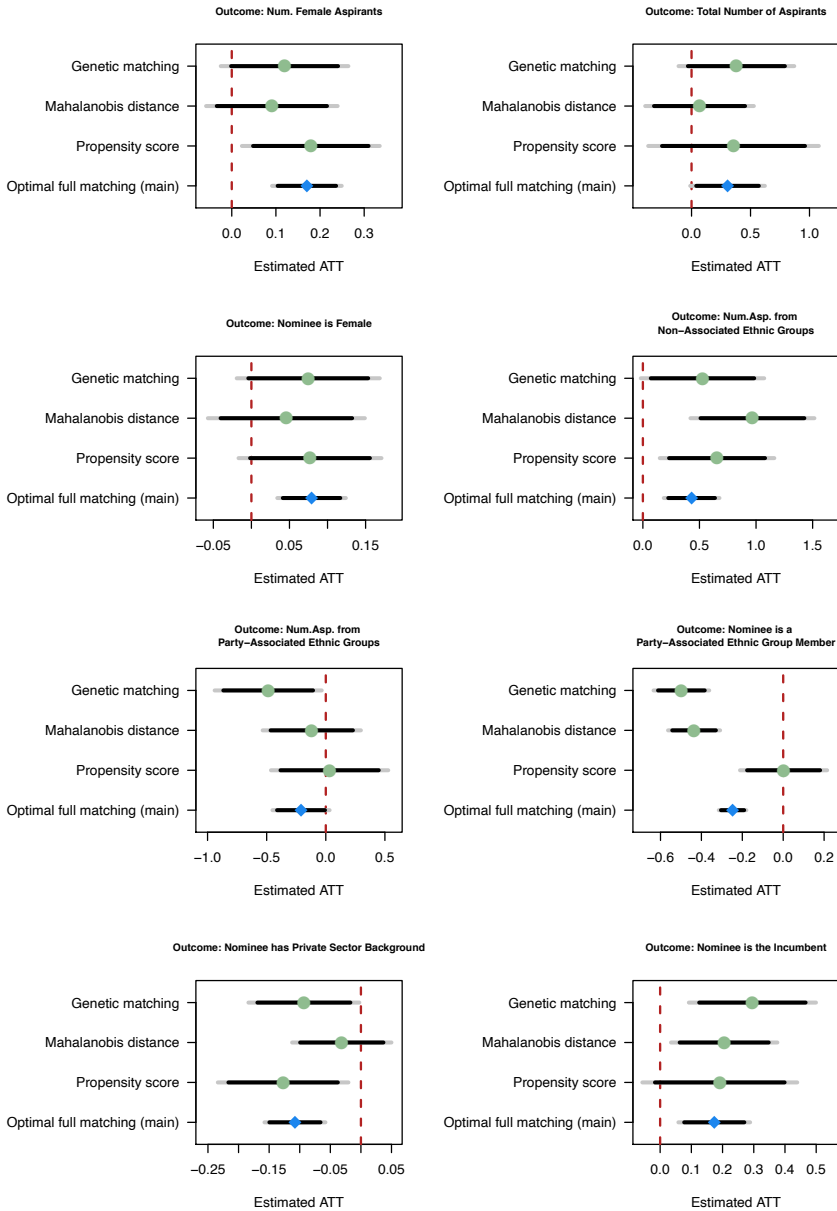


Figure C4: Estimated ATT with Alternative Matching Methods. The circles indicate the estimated effect, with the darker and lighter lines indicating 90% and 95% confidence intervals, respectively.